An investigation of pre harvest inventory methodology at varying intensities conducted in Omihi Forest, Canterbury, New Zealand

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Shaun Coles

School of Forestry, University of Canterbury
New Zealand

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Abstract

New Zealand forestry has used current pre-harvest inventory (PHI) procedures for a very long time. With developing technology, such as LiDAR, management of forest estates should become more site-specific, hence the implementation of precision forestry (Dash, et al., 2016). Precision forestry requires higher spatial precision in estimates of productivity indices such as 300 index and site index. Both indices rely heavily on estimates of mean top height (MTH) at age 20 for a stand of *Pinus radiata* (D.Don).

Mason (2019) investigated the effects on estimates of MTH of fitting the height-diameter (H-D) relationship at a plot-level compared to the current standard, at stand-level. Stand-level fittings of the H-D relationships artificially reduced MTH standard deviations and violated the assumption of independent sampling units, when compared to plot-level fittings of H-D relationships.

The study reported here compared a range of height numbers measured (3, 6, 9, 12, and all) per plot, in order to fit H-D relationships at both a stand-level and plot-level, at a range of plot sizes (0.04, 0.06, 0.08, and 0.1 ha). Relevant costs (measured in time) associated with each different plot size and number of heights were balanced against increases in accuracy (compared with estimates obtained when all heights were measured) for those variables involving heights, and precision for all four key variables; stocking (N), basal area (G), volume, and MTH with increasing plot size and/or numbers of heights measured per plot.

Plot size did not significantly affect standard deviations of estimations of volume or MTH. However, increases in height measurements/plot did not add unjustifiably large costs, and mean absolute value of errors of MTH estimation was markedly reduced by measuring more than three height trees per plot. Analyses conducted by Mason (2019) were replicated yet produced larger absolute values of errors in MTH estimation were lower at plot-level fittings of H-D relationships.

Keywords: pre harvest inventory, plot size, height, mean top height, estimates, precision forestry.

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Introduction

Forest Inventory

Forest Pre-harvest Inventory (PHI) has long been a key part of the tactical planning phase that enables optimisation of harvesting systems and grades for maximum value recovery. A common tool used for inventory analysis and optimization in New Zealand is an innovative piece of software from Interpine Innovation known as YTGEN, written by Brian Rawley. This software provides algorithms for generating yields from forest inventory data, applying height and diameter at breast height (dbh) regression to the inventory data, projecting estimations of volume and taper, and estimating breakage and stumpage. While PHI is used frequently in the forest industry, very little research has focused on optimising it. While many inventories are conducted by the industry, PHI is arguably the most important, given its temporal proximity to harvest.

The issue that this study addressed was limited information surrounding the effect of intensity of PHI has accuracy of stand estimates of mean top height (MTH), basal area/ha, stems/ha and volume/ha. A study by Mason (2018) investigated two modes of calculating MTH, both when height-diameter (H-D) relationships used to estimate unmeasured heights in plots were fitted at a stand-level and when H-D relationships were fitted at a plot level. This is the most recent study of inventory procedures, and it addresses the process of finding optimal methods for conducting inventories to desired levels of precision. The methodology of PHI collection has been unchanged for a long time, and there are underlying issues surrounding the intensity of our current inventory procedures (Lee & Goulding, 2002). While yields may be generated from the inventory, they depend on accuracy of the data, hence the need to rethink how intensive we are prepared to become with PHI procedures in order to derive more accurate metrics. Current procedures which involve fitting a stand-level H-D relationship have also been shown by Mason (2018) to provide substantial error in estimations of MTH variance within stands.

The recurring issue surrounding the intensity of PHI is related to the willingness of a forest owner to pay more for more reliable forest metrics. Given the different tastes and preferences of every owner, there is no single set of forest inventory procedures investigated in this study which would suit everyone's desires. Consequently results reported here will allow managers to make better informed decisions about inventory intensity.

Research Questions

- Do plot size and/or different numbers of height measurements/plot, influence accuracy (assessed as comparisons with estimates when all heights in plots are measured) or standard deviations of basal area/ha (G), stems/ha, mean top height (MTH) and stem volume within an inventory?

- How do plot size and or numbers of height measurements/plot influence time required for plot measurement?

- Are there statistical, financial and/or practical benefits of measuring fewer but larger plots with more heights per plot for inventories of forest stands?

Literature Review

Forest Inventory

Forest inventory is the process of measuring a forest in order to provide estimates of standing volume and other important stand variables such as basal area/ha, stems/ha and mean top height (MTH). In New Zealand, pre-harvest inventory (PHI) is a fundamental part of the marketing of wood commodities and products as it enables both parties involved in a transaction to have an accurate assessment of the resource (Cooke & Webster, 2005). New Zealand PHIs have traditionally employed MARVL (method of assessing recoverable volume by log type) inventories in order to quantify the resource accurately (Deadman & Goulding, 1979). MARVL inventories employ dictionaries of defects to code stems in a manner which enables programs such as YTGEN (Lusk, 2007) to produce yield tables containing estimates of yields by log grade.

MARVL inventories require a particular sampling and plot measurements. Deadman & Goulding (1979) noted that plots must be stratified in one of the three following ways: simple random sampling, stratified random sampling with one H-D relationship fitted for the population, and stratified random sampling with separate H-D relationships fitted for each stratum. Within a stand, it is tough to establish different strata because there are so many variables that can influence segregations in strata.

Systematic Plot Layout

While there are some doubts about the independence of systematic sampling methods (Kangas, 2006), there is still a randomness to the distribution of the plots within an inventory with respect to variation in stand condition (Köhl, Magnussen, & Marchetti, 2006). Provided the starting point and orientation of a systematic sample is chosen randomly, it is accepted that a systematic selection of plot locations may be considered as random and independent (Gordon, 2006). However, a systematic layout of plots should not fall along spatial patterns such as ridges or contours because this could cause estimates to be significantly biased.

There are a number of practical reasons for installing plots in a systematic manner. For example, locations of plots can be difficult especially because receiver accuracy of a GPS is diminished under a canopy (Eggleston 1992). While this is a somewhat dated study, Trimble (2018) recently found that "multipaths" resulting from non-direct lines of site from satellites to receivers, is the largest cause of receiver error. While inventory crews carry GPS units through forests, they are generally not survey grade and so in addition to multipath error, there is also the issue of lower quality receivers being utilised (Lachapelle & Henriksen, 1995). By adopting a systematic plot layout, the pattern of plot centres becomes more predictable for the crew and location of plots therefore becomes much easier. With a fully random plotting approach, crews would rely on GPS unitsand as canopies of *Pinus radiata (D.Don)* are typically dense at age 20, precisely locating plot centres would be very difficult.

Plot Size

Generally, PHI plots are circular because such plots are easier to set up than rectangular ones (Gordon, 2006) (Hayes, 2006). The vertex rangefinder makes circular plots exceptionally easy to measure, for all that is required is a centre peg, a vertex, a transponder, and the known radius for the given plot size and slope. No tapes are required to ensure accurate boundaries are established. A circular method also minimises bias with regards to orientation within the plot as there is a roughly equal spatial distribution of trees surrounding plot centres.

When considering what factors affect the accuracy of estimates generated during inventory, plot size is a logical factor to study. A study which targeted plot size for efficacy of samples for forest attributes found that aggregated patterns of plots lowered sampling precision and that wide spatial distribution was more important than clusters (Zhengyang, et al., 2015). While Zhengyang et al.'s study addressed larger plot sizes, no conclusions were drawn about the accuracy of estimates from data collected in larger plot sizes, merely that a wider spatial distribution, ie, number of plots is one of the most important drivers of inventory accuracy.

Height Measurements

MTH is defined as the mean height of the 100 largest dbh trees per hectare. This measure is used extensively within forest modelling and mensuration. Site index is the MTH of a stand of *Pinus radiata* at age 20, or age 40 for *Pseudotsuga menziesii*. Goulding (2006) reported that while site index is an easily measured estimate of productivity, there is a large amount of variation in estimates of site index between species and regions. He also found that substantial error can occur during the process of calculating MTH. This variation limits the usefulness of site index as a measure of productivity, meaning there is great potential to find ways for reducing error of MTH calculations in order to provide more stable estimates of site productivity using site index.

One of the largest contributors of error in MTH calculations is the trees selected to be measured for fitting an H-D regression which is used for estimating unmeasured heights of trees. The H-D relationship varies substantially within and between *Pinus radiata* stands. Typically a wide range of heights are found for similar diameters within a radiata plantation. As a result of this variation, trees need to be selected for height measurement across the diameter range while any extra trees measured need to be selected by favouring larger diameters in order to explain as much variation of H-D relationships as diameter increases as possible (Goulding, 2006).

While the trees selected for heights are important, there are several other factors that can lead to variation in MTH estimation. One in particular is the Naslund (or Petterson) equation being fitted at either a plot-level or stand-level. A recent study by Mason (2019) highlighted issues surrounding stand-level fittings of the H-D relationship. In summary, fitting H-D relationships at stand level is analagous to violating the assumption of independent sampling units. However, PHIs typically involve measurements of three tree heights per plot to estimate heights using the Naslund equation, therefore returning a very limited number of observations from each plot to create a relationship. More intensive Permanent Sampling Plots (PSPs) typically involve at least 12 tree height measurements per plot. By fitting the H-D relationship at a plot level, sampling units, or plots, are fully independent and so more realistic estimates of sampling variation are likely to be produced. The key issue, as identified by Mason (2019) is that a typical PHI potentially does not measure enough height trees per plot in order to make effective H-D relationships at a plot-level.

Time Study

Conducting a time study is an important part of an operational efficiency analysis. There are a wide range of factors that influence the productivity of any given forest inventory. It is difficult to express in a general manner which factors may have the largest influence on cost of any given PHI, for each stand is different and different factors may influence time taken. However, a key factor appears to be the plot size established. Nowak, Walton, Stevens, Crane, & Hoehn (2008) found that increasing plot size from 0.04 ha to 0.067 ha led to a 27% increase in the time taken to measure each plot. The major driver of the increase in time taken arose from the extra number of trees measured, while another factor was the extra distance travelled between plots if plot numbers were reduced.

Light Detection and Ranging (LiDAR)

Precision forestry refers to the implementation of modern technology in order to gain site-specific understanding of our forests for management purposes (Dash, et al., 2016). Precision forestry has been encouraged by precision agriculture which involves a combination of various mensuration systems such as geographic positioning systems (GPS), geographic information systems (GIS), remote sensing methods such as Light

Detection and Ranging (LiDAR), and field evaluation in order to make more finely grained operational decisions within sites. The implications of precision forestry extend further than for agriculture (Mason, Morgenroth, & Bown, Precision Forestry Research Project, 2016). Development of LiDAR technology has increased the potential of precision forestry. Estimating productivity indices such as site index and 300 index using LiDAR provides a forest manager with the flexibility to view the resource holistically and derive more spatially stratified information (Dash, et al., 2016). Increased resolution of details affecting forest management decisions will allow more site-specific forest management.

While there is enormous potential for LiDAR to influence forest inventory, there are a number of logistical and financial issues (Wulder, Bater, Coops, Hilker, & White, 2008). The increase in cost of measurement through the use of LIDAR makes precision forestry impractical for many owners. A study by Hummel, Hudak, Uebler, Falkowski, & Megown (2011) highlighted that LiDAR measurement was about five times the cost of field measurement alone. The benefit of LiDAR in this situation, however, was the capture of a detailed description of the whole forest compared to the partial capture by an inventory field crew. A compounding issue for precision forestry is the requirement for both field measurement and LiDAR measurement. In order to fit LiDAR metrics, field metrics need to be taken to "ground truth" the LiDAR data (Slui, 2014). A key issue for the implementation of LiDAR data, identified in a dissertation study by Slui (2014), is that co-registration errors, or locational errors, have a significant impact on the utility of LiDAR canopy metrics due to poor matching with field measurements at ground level.

Methods

Research tests

Given that the research questions address the most efficient plot size and number of height trees measured to fit a height-diameter relationship, there were 20 iterations of data collection. There were four plot sizes of 0.04, 0.06, 0.08, and 0.1 ha, and five height measurement intensities: 3, 6, 9, 12 and all trees measured per plot, hence the 20 repetitions as follows:

A – 0.04 ha plot size with 3 height trees used to fit the height-diameter regression.
B – 0.04 ha plot size with 6 height trees used to fit the height-diameter regression.
C – 0.04 ha plot size with 9 height trees used to fit the height-diameter regression.
D – 0.04 ha plot size with 12 height trees used to fit the height-diameter regression.
E – 0.04 ha plot size with ALL height trees used to fit the height-diameter regression.
F – 0.06 ha plot size with 3 height trees used to fit the height-diameter regression.
G – 0.06 ha plot size with 6 height trees used to fit the height-diameter regression.
H – 0.06 ha plot size with 9 height trees used to fit the height-diameter regression.
I – 0.06 ha plot size with 12 height trees used to fit the height-diameter regression.
J – 0.06 ha plot size with ALL height trees used to fit the height-diameter regression.
K – 0.08 ha plot size with 3 height trees used to fit the height-diameter regression.
L – 0.08 ha plot size with 6 height trees used to fit the height-diameter regression.
M – 0.08 ha plot size with 9 height trees used to fit the height-diameter regression.
N – 0.08 ha plot size with 12 height trees used to fit the height-diameter regression.
O – 0.08 ha plot size with ALL height trees used to fit the height-diameter regression.
P – 0.1 ha plot size with 3 height trees used to fit the height-diameter regression.
Q – 0.1 ha plot size with 6 height trees used to fit the height-diameter regression.
R – 0.1 ha plot size with 9 height trees used to fit the height-diameter regression.
S – 0.1 ha plot size with 12 height trees used to fit the height-diameter regression.
T – 0.1 ha plot size with ALL height trees used to fit the height-diameter regression.

Study Location and Study Subjects

Buck Forestry Services took an intensive inventory of compartment 12 of Omihi forest. It was imperative that data were collected by a professional team as there are elements of a time study associated with data collection and any inventory conducted by a non-trained professional would not represent the industry standard.

Omihi Forest is located approximately 8 kilometres North West of Amberley, Canterbury, New Zealand. Being a coastal forest, there is little understorey vegetation (Campbell, 2011). Saline wind inhibits the growth of weeds throughout much of the forest as *Pinus radiata* (D. Don) strongly outcompetes any understorey vegetation with the exception of weeds in a few gully sites.

This study was conducted within Omihi Forest for several reasons. Firstly, it was a practical location to commute to from the University of Canterbury, being approximately a one-hour commute by vehicle. As this was a relatively unprecedented and intensive study, it was essential to allocate ample time for data collection. The second reason Omihi was chosen was due to the demographic of the selected stand. Having PHI conducted recently, in April, meant that the data collected during this initial PHI could be utilised and combined with additional data, extending plot sizes and numbers of height measurements enabling a less costly study with essentially no effect of delayed data collection. The third reason was that the stocking and open nature of the understorey allowed for an accurate time study to be conducted with minimal competitive vegetation impedance.

Buck Forestry Services provided two employees to measure trees, and their work was timed. For the purposes of this study, they will be referred to as worker A and worker B. The time study involved several elements; time to walk to a plot, time to set out a plot by measuring the distances to each tree, time to measure the height of each tree, time to measure the diameter of each tree, time to walk to a position to stem description of each tree, time to record a stem description of each tree, and time to walk between trees within a plot. An impromptu column was also added during the data collection for any time spent amending mistakes.

Process

The process of conducting an inventory can be broken into 4 key steps; plot location, plot setup, plot measurement, and plot conclusion.

Inventory began by walking to the plots which had already been established during Pre-Harvest Inventory (PHI). This was the key element of the plot location step. Plot sizes established during PHI to reach the 18 trees per plot requirements for Rayonier Matariki Forests were 0.04 hectares, as the stand averaged roughly 500 stems per hectare. Upon arrival, plots were laid out. Given the earlier inventory for PHI, the plot centre was already established and numberings were already assigned for trees within the 0.04 ha plot. This meant that set up for data collection was simpler than if it had been done from scratch. The key part of plot setup for this study was conducted by Worker A who combed through each tree that was outside the boundary of the 0.04 ha plot and measured the distance to each one using the vertex clinometer as the instrument, while worker B held the transponder for the vertex at 1.4 metres high over the centre of the plot. Each plot was located on different slopes and so the plot radius was adjusted based by this slope, as is industry standard, using the following formula:

Equation 1: $radius = squareRoot(plotArea/(\pi\ cosine(slope)))$

A time was recorded for the measurement of distance to each tree. Typically, not all trees are measured for distance when setting out a plot during inventory (specifically trees that are obviously within the plot radius). It was important that the data included a spatial reference for each tree in order to differentiate between plot sizes, hence all trees within the 0.1 ha plots were measured for distance except for the premeasured trees within the 0.04 ha plot size. While the distance measurement occurred, trees were numbered by worker A as a sequential sweep was conducted, giving the numbering order. Numbers for the collection of trees outside of the 0.04 ha plot size began with the superseding number of the last tree in the 0.04 ha plots already measured. All numbering was performed using white spray paint. Any trees that were close to the boundary were measured with a tape. The time taken to do this was accounted for in the time study as it is realistic to get one or several 'tape' trees in a plot.

Following plot set-up, the actual plot measurement was conducted. The key variables measured were dbh, height, distance to plot centre, and stem description. The process involved worker B shifting around the plot, numerically, placing the transponder at 1.4 metres above ground level on each tree, allowing worker A to shoot the height and produce a stem description. Once the transponder was placed on the trunk, and while worker A shot the height and took a stem description of the tree, worker B measured the dbh. It was assumed that measurements recorded were not different from actual values. This assumption may not hold for height because it is difficult to measure due to wind, the crown form, visibility, and the distance to the top of the tree.

While the workers conducted this phase of the inventory, the time taken for worker A to navigate around the plot to get in a position to shoot the height with the vertex, and the time to shoot it were measured. The time for worker A to take the stem description was also recorded. While the diameter is important, it is generally measured in the time it takes to provide a stem description, or in this case, time to provide a stem description and record the heights. The resulting time element for diameter recording is simply the amount of time it took worker A to enter the diameter, that worker B communicated, into an Allegro field computer. An important assumption for my work time study was that regardless of whether a height measurement was conducted in any given inventory that it was quicker to measure the diameter than take a stem description.

Following the completion of all trees in a plot, there was a short lag period to check the quality of work to ensure no trees were missed or double numbered. The segment of the time study that accounted for this was an extra "impromptu" element. The process was repeated for all 25 plots; however, the work time study was conducted only for 12 of the plots. The reasoning behind this was that in order to conduct an efficient and accurate time study, the process needed to be fully observed and all elements accounted for, and timing 12 plots was considered an adequate sample.

Anomalous plots

Broken topped, dead, or double stem/leader trees are commonly encountered during inventories. Typical inventories are conducted in accordance with the PlotSafe Forest Inventory Procedures Manual (CNI Regional YTGEN User Group, 2007). Broken trees, in accordance with section 4.1.7 of the manual, are coded in the Allegro field computer as being broken. This was entered in the 'height status' column as "BROKEN". If a tree was dead, but still merchantable as pulp, the tree was coded as "DEAD" in the 'is alive' column. If the tree was unmerchantable, it was excluded from inventory.

Data Analysis

The data were stored in a comma-separated variable, text file format. Data analyses were conducted using R Statistical Software (R Core Team, 2013). Prior to importing the file to R, the '.csv' file was edited to define different plot extents. The individual plot average slopes were entered, and a corresponding critical distance was created which denoted the upper and lower radii limits for the four different plot sizes of 0.04, 0.06, 0.08, and 0.10 ha. This utilised the slope adjustment equation (equation 1).

Columns denoting whether a tree was in each plot size were created; 'is_0.04ha', 'is_0.06ha', and 'is_0.08ha' were the columns as any data within the file was considered in the 0.1 ha plot. These columns were given logical values of true or false in order to make filtering data for the creation of different plot sizes easier. Subsequent dummy variables were used later in the analyses which were given values of 1 if the 'is_0.x ha' was true, or values of 0 if 'is_0.x ha' was false.

A series of samples for different numbers of height trees at different plot sizes were created. Given the 5 different numbers of heights used to create the height-diameter relationship, and 4 different plot sizes, there were a total of 20 sampling runs were created for each plot. Common practice for choosing height trees in inventory is to select trees across the range of diameters, while prioritising extra trees measured among larger diameters. In order to ensure that the trees selected in the sample represented the entire diameter range, the largest and smallest diameter trees were selected for the sample of heights measured within each plot. In order to ensure an accurate height-diameter relationship for each plot size and height measurement intensity, trees recorded as broken or dead were excluded from the samples used to fit height-diameter relationships. The trees that were selected for the sample of heights measured for each of the various numbers of heights measured per plot at the four different plot sizes were assigned a value of 1, while those not selected were assigned a value of 0.

Multiplying the height (m) of every tree by the binary variables assigned to the sample of heights measured per plot for different plot sizes either provided no return for the corresponding variation if it was excluded from the sample, or returned the measured height of the tree for the corresponding variation if it was included in the sample of heights measured per plot at different plot sizes.

Some plots had many broken trees, such as plot 11, and therefore had too few trees in the plot to fit an H-D relationship using 12 and 9 trees. In these instances the closest tree with a height measurement to the plot centre which fell outside the confines of the given plot was added into the set used to fit H-D relationships. The H-D relationship was fitted at both a plot-level and a stand-level in order to generate coefficients to enter into the Naslund equation (see equation 2) which was then used to estimate heights of every non-measured tree for each of the 20 variations of plot size and height numbers measured.

Equation 2: $H = 1.4 + (b + a/dbhob)^{(-2.5)}$

As the dataset which had assigned samples for height trees being measured in each of the different scenarios, and remaining heights had been estimated using the Naslund equation, variables could be estimated at a tree and plot level. A volume equation was fitted to each individual tree (see equation 3). The volume equation used was an individual tree equation; the "All NZ (Not Sands)" equation, extracted from New Zealand Forest Research Institutes' Forecaster software (2017).

Following estimation of individual tree volumes for each tree in all 20 variations of plot size and height numbers, plot estimates were derived. Plot basal areas per hectare (G) were estimated by summing all basal areas for individual trees and dividing the sum by plot size. Plot stockings per hectare were estimated by summing the count of all "true" returns to the "is_0.x_ha" columns for each plot and dividing by plot size. This count was affected by the state of mortality in the stand as any broken or dead tree was excluded from the stocking count. Volumes per plot were calculated by summing individual tree volumes and dividing by plot size. MTH was estimated per plot by fitting the CHH MTH equation which is the average height of the largest 100 diameter trees per hectare, regardless of estimation or actual measured heights.

Equation 3: $V = H * G * (B1 * (H - 1.4) ** (-B2) + B3)$

Where: *B1= 8.60000E-001*

B2= 9.72000E-001

B3= 3.04000E-001

Standard deviations between plots and probable limits of error of stand means (PLE) of all variables were calculated, yielding 20 different sample standard deviations, one for each combination of plot size and number of height trees. In addition to standard deviations, absolute errors were also generated between MTH estimates. The actual MTH for a plot was assumed to be the MTH derived from actual tree height measurements of the 100 largest diameter trees/ha. This was used to calculate the absolute value of the error of MTH estimation for each combination of number of measured heights and plot size. Absolute values of errors and standard deviations were calculated for estimates when the H-D relationship was fitted at both stand-level and plot-level. Analysis of variance was used to compare estimates of absolute value in error of MTH, as well as standard deviations generated for each of the 20 variables.

MTH values estimated at a plot level were analysed in a linear mixed effects model with both plot size and numbers of height trees measured per plot as factors, and plot id as a random effect. Following the fitting of the mixed effects model, pairwise comparisons were made in order to explore which numbers of heights measured per plot produced statistically significant differences in MTH estimations and whether there were any significant differences in MTH estimations for different plot sizes.

The times generated during the time study conducted in the field were analysed in R Statistical Software (R Core Team, 2013) in order to derive the total time taken to conduct full inventory on one tree. Given that the time study was only conducted for 12 of the 25 plots at a plot size of 0.1 ha, and the trees that were measured in the initial PHI conducted earlier in the year, entailing all trees within the 0.04 ha size, were also unaccounted for; there was only a partial representation of all observations.

In order to accommodate for the missing times, time elements for both the stem description and height measurements were estimated for each tree. Both time elements for stem description and height measurement were estimated using individual tree heights (m) as height (m) significantly affected the time taken to measure heights. This process involved using a scaled power transformation on each of the time elements and the height (m) in order to fit a linear model. Following the transformation, models were fitted in a mixed effect analysis of variance with plot as a random effect and regressing time to measure each tree versus measured height. The same analysis was conducted for time to measure the stem description of each tree. By backwards transforming, a time element could be estimated for both time to measure height and time to measure the stem description for each tree.

The remaining time elements for time to walk to and measure the distance to plot centre, time to record diameter, and any excess miscellaneous time were merely averaged in order to derive a per tree time for each of these elements as they were found to be independent of the measured tree variables such as height (m) or dbh (mm) by running an analysis of variance test.

Following the calculation of individual tree times for every observation in the study, times could be estimated for each plot for the full range of plot sizes and numbers of height trees measured per plot. Given that only a subset of the trees were within the boundaries of each of the plot sizes, except for the 0.1 ha plot size which held all observations, dummy variables of 1 and 0 were used in order to calculate total time taken per tree for each plot size. If the tree was in the desired plot size, the sum of time elements, excluding the time to measure height, was multiplied by 1, and if not, was multiplied by 0 in order to return no time value for that tree and excluding it. A similar process was followed to create time values for instances of different numbers of height trees measured per plot for each of the plot sizes. Dummy variables of 1 and 0 were again assigned to trees that were selected for each of the five different numbers of heights measured per plot. By multiplying the time element for height measurement by either 1, or 0, the tree was either given the additional time taken to measure the height, or not. For the instance of full height measurement for each of the plot sizes, all height measurement time elements were multiplied by 1, and the corresponding dummy variable for plot size in order to ensure that all times for heights were included, provided they fell within the desired plot extent.

Following the reconstruction of individual tree times, times per plot for the range of plot sizes and numbers of heights measured per plot were generated by summing the total time for each tree. If a tree did not fall within the plot size, the time that was added was 0, meaning only the trees which fell within the desired plot size, or were selected for height measurement for the respective numbers of heights measured, was summed. These plot level time estimates were then averaged in order to derive an expected time for each of the 20 variations of plot size and number of heights measured. Using these times, a mixed effects analysis of variance model was created with time to measure plots as a dependent variable, plot size and numbers of heights as factors and plot as a random effect in order to determine whether or not plot size and numbers of measured heights significantly influenced time/plot.

Results

Estimates of volume, mean top height calculated at a plot-level, basal area and stocking are displayed below in *Table 1*. The larger plot sizes 0.06, 0.08 and 0.10 ha all have relatively similar estimates for these four key variables, potentially indicating that larger plot sizes may produce more realistic, or repeatable results.

Table 1: Estimates for volume, mean top height, basal area and stocking based upon data generated for the four different plot sizes with all heights measured.

Plot Size (ha)	**Volume (m3/ha)**	**MTH (m)**	**G (m2/ha)**	**N (trees/ha)**
0.04	531	30.34	54.4	446
0.06	516	30.37	52.6	427
0.08	519	30.62	52.7	428
0.10	520	30.62	52.7	428

Table 2 shows that there were variance of plot MTH was not significantly influenced by plot size. Given that variances were not significantly different at varying numbers of heights measured per plot, the PLE term was also not significantly different as it is partly a function of standard deviation.

Table 2: P-value test results for significant differences between different standard deviations calculated for changing plot size, at a range of height number measurements.

Are standard deviations of plot size significantly different at various height numbers					
Height Numbers (per plot)	**3**	**6**	**9**	**12**	**All**
Bartlett P-Value	0.9116	0.8765	0.9943	0.9828	0.9544
Fligner-Killeen P-Value	0.8651	0.9014	0.9814	0.9984	0.9594

Table 3 shows that variance in plot MTH was not significantly influenced by numbers of heights measured. The analysis was run in order to test if there was a difference in standard deviation of MTH between plot sizes for a variety of different height measurements per plot. The findings the Bartlett test of homogeneity of variances, and Fligner-Killeen test of homogeneity of variances both show that there are no statistical differences between estimations of MTH at different plot sizes for the full range of height measurements per plot employed.

Table 3: P-value test results for significant differences between different variances calculated for changing plot size, at a range of height number measurements.

Are standard deviations of height numbers measured significantly different at various plot sizes				
Plot Size (ha)	**0.04**	**0.06**	**0.08**	**0.10**
Bartlett P-Value	0.7418	0.7840	0.8611	0.8008
Fligner-Killeen P-Value	0.7321	0.6529	0.7524	0.9659

The following table provides the p-values for the slope of the linear model for the regression of the standard deviations of MTH at varying plot sizes when different numbers of heights measured per plot are removed as factors. As shown, the slope is not statistically different from 0 for each of the different height number factors between 3 and 12, however, for when all heights were measured, there was a statistically significant slope on the regression between plot size and standard deviation of MTH estimation. The significant slope for all height numbers measured when regressing standard deviation of MTH by plot size was –0.243, meaning that as the plot size increased the standard deviation of MTH decreased.

Table 4: P-value test results for linear regression slope being significantly different to 0. The x variable is plot size while standard deviation is the response.

Are there any significant trends in standard deviation as plot size changes for a range of height measurements?					
Height Numbers (per plot)	**3**	**6**	**9**	**12**	**All**
Linear regression P-Value	0.1194	0.1932	0.1524	0.2336	0.0164

Table 5 denotes the p-values for the slope of the linear model which regresses standard deviations of MTH fitted at a plot-level against the number of heights measured to fit the H-D relationship. The four different plot sizes measured have been factored out in order to provide individual statistical significance values for each of the four plot size variants. As shown for each of the four different plot sizes, the slope of the linear model for the regression between standard deviation of MTH and number of heights measured per plot was greater than 0.05 and was therefore not significantly different from 0. This means that there was no statistical trend between the number of heights measured and the standard deviations of the MTH.

Table 5: P-value test results for linear regression slope being significantly different from 0. The x variable is height numbers measured per plot while standard deviation is the response. Plot size has been factored out.

Are there any significant trends in standard deviation as height measurements change for a range of plot sizes?				
Plot Size (ha)	**0.04**	**0.06**	**0.08**	**0.10**
Linear regression P-Value	0.3361	0.2824	0.2254	0.2098

Pairwise comparisons were performed for the linear mixed effects models for MTH with plot size and number of heights measured per plot as factors and plot as a random effect. The results are displayed in *Table 6*, below, which indicate that there is a statistical difference between the means of the various numbers of heights measured. That difference occurs between three heights measured per plot and the rest of the investigated numbers of heights/plot.

Table 6: Pairwise comparison for linear mixed effects model of MTH with number of heights measured as a factor and plot as a random effect.

Height Numbers	Emmean	Std. Error	Degrees of Freedom	Lower Confidence Limit	Upper Confidence Limit	Group
3	30.1	0.455	24	29.1	31.0	a
6	30.4	0.455	24	29.5	31.4	b
9	30.5	0.455	24	29.5	31.4	b
12	30.6	0.455	24	29.6	31.5	b
All	30.5	0.455	24	29.5	31.4	b

Figure 1, below, provides more information about the H-D relationship fitted at a stand-level when compared to one fitted at a plot-level. The graph shows that there were smaller absolute errors in the height estimations as the number of height trees measured to fit the H-D relationship increased. This graph also shows that the plot-level fittings of the H-D relationships were more accurate than the stand-level fittings of the H-D relationship.

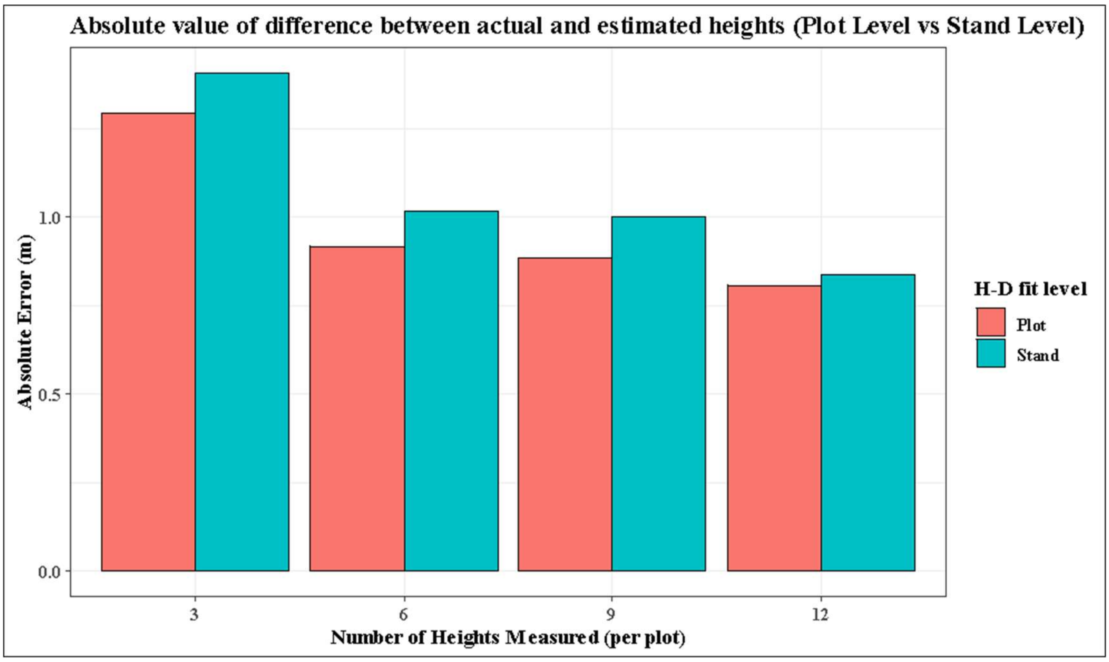

Figure 1: Mean absolute values of error for estimated mean top (?) heights when actual measured heights are considered. Errors are amalgamated between different plot sizes and are displayed for different numbers of height trees measured to fit H-D relationship.

Figure 2 shows that measuring more than three height trees per plot to fit the H-D relationship provided a lower mean absolute value of error when the residuals were derived from comparing the MTH estimates against the MTH estimates with all heights measured. There was no clear trend in absolute value of error of the estimations with plot size, except that the smallest plot size generated the largest absolute errors for all numbers of heights measured. At a plot size of 0.04, 0.06, and 0.1 ha there was no statistically significant trend in the absolute value of error in MTH estimation as number of heights measured per plot increased. However, at a plot size of 0.08 ha there was a statistically significant trend in the absolute value of error in MTH estimation as number of heights measured per plot increased, as shown below in *Table 7*. The p-value for the slope of the linear model for plot size of 0.08 ha of 0.031 means that the null hypothesis cannot be rejected and that the slope of the linear model was significantly different to 0. The slope for the linear model was –11.187, meaning that in order to reduce the absolute value of error in MTH estimation by one metre, the number of height trees measured needed to increase by 11 trees per plot.

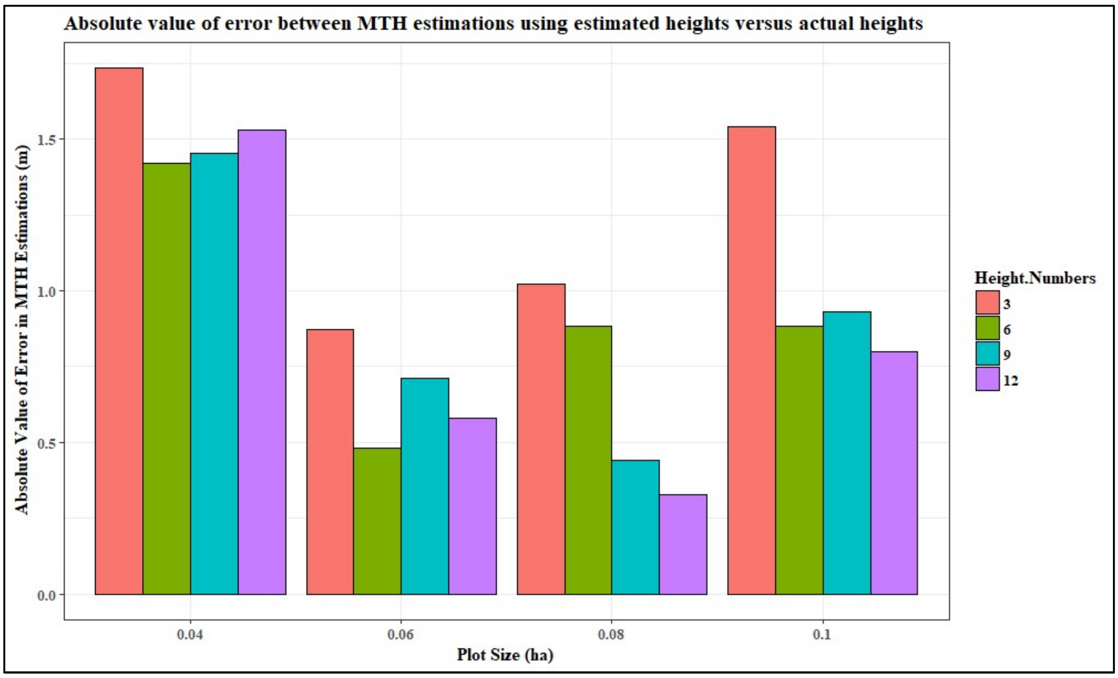

Figure 2: Mean absolute value of error in estimating mean top heights when actual measured tree heights are considered as a standard. Errors are segregated for different plot sizes and are displayed for different numbers of height trees measured to fit H-D relationship.

Table 7: Test for statistical significance of the slope of a plot size of 0.08 ha, where the x variable is heights measured per plot and the y variable is the absolute value of the error in MTH estimation.

	Estimate	Std. Error	t value	Pr (>|t|)
Intercept	14.979	1.460	10.261	0.009
Absolute Value of Error in MTH estimation	-11.187	2.002	-5.587	0.031

Increasing height numbers measured decreased the absolute value of error in MTH estimation for a range of plot sizes. However, *Table 8* presented below shows there to be a significant difference when the various plot sizes are amalgamated, and the height numbers are tested alone. The Tukey's honest significant difference (HSD) test showed that there was a significant difference between 3 heights measured and the rest.

Table 8: Pairwise comparison using Tukey's Honest Significance Difference (HSD) test for differences in the absolute value of error in MTH estimation for various numbers of heights measured.

Heights measured per plot	emmean	Std. Error	Degrees of Freedom	Lower Confidence Limit	Upper Confidence Limit	Group
12	0.810	0.463	24	-0.1466	1.77	A
9	0.884	0.463	24	-0.0722	1.84	A
6	0.917	0.463	24	-0.0397	1.87	A
3	1.292	0.463	24	0.3352	2.25	B

The same Tukey's HSD test was conducted for plot size. *Table 9*, below, provides some interesting results; with 95% confidence, the largest mean absolute error in MTH estimation was found to be from the smallest plot size of 0.04 ha. This was significantly more error than the other three plot sizes measured. However, the next least accurate fitting of MTH was found to arise from the 0.1 ha plot size, with a mean error of 1.04. The middle two plot sizes had the smallest absolute errors in the MTH estimation.

Table 9: Pairwise comparison using Tukey's HSD test for differences in the absolute value of error in MTH estimation for various plot sizes measured.

Plot Size	emmean	Std. Error	Degrees of Freedom	Lower Confidence Limit	Upper Confidence Limit	Group
0.06	0.661	0.463	24	-0.2952	1.62	A
0.08	0.669	0.463	24	-0.2879	1.63	A
0.1	1.039	0.463	24	0.0822	2.00	B
0.04	1.534	0.463	24	0.5776	2.49	C

The work time study conducted on site was manipulated in order to achieve estimates of total cost, in minutes per plot, for each of the 20 different combinations of plot size and number of height trees measured. This time study data is presented in *Figure 3*, where there appears to be a trend that shows only a minor increase in cost for increasing the number of height trees measured in increments of three. The fastest inventory method, as shown below in *Table 10*, was a plot size of 0.04 ha with only three height trees measured to fit the H-D relationship. This combination had an average time of 32 minutes per plot. As number of heights measured increased in increments of three, there was an increase in time per plot of approximately 1.5 minutes, meaning that measuring 12 height trees per plot had a mean time of 37 minutes per plot. However, when measuring all trees for height in any given plot size, there was a significantly larger time taken compared to 12 height trees per plot.

This trend was replicated across all plot sizes. As the plot size increased in increments of 0.02 ha, was a significant increase in the time per plot, however, the rate that this time increased by was determined by the stockings at each of the different plot sizes. For example, it can be seen that as the plot size increased from 0.04 ha with all heights measured to 0.06 ha with all heights measured, there was an increase of 19 minutes, however, when increasing the plot size by the same increment of 0.02 ha, to 0.08 ha with all heights measured, there was an increase of 20 minutes.

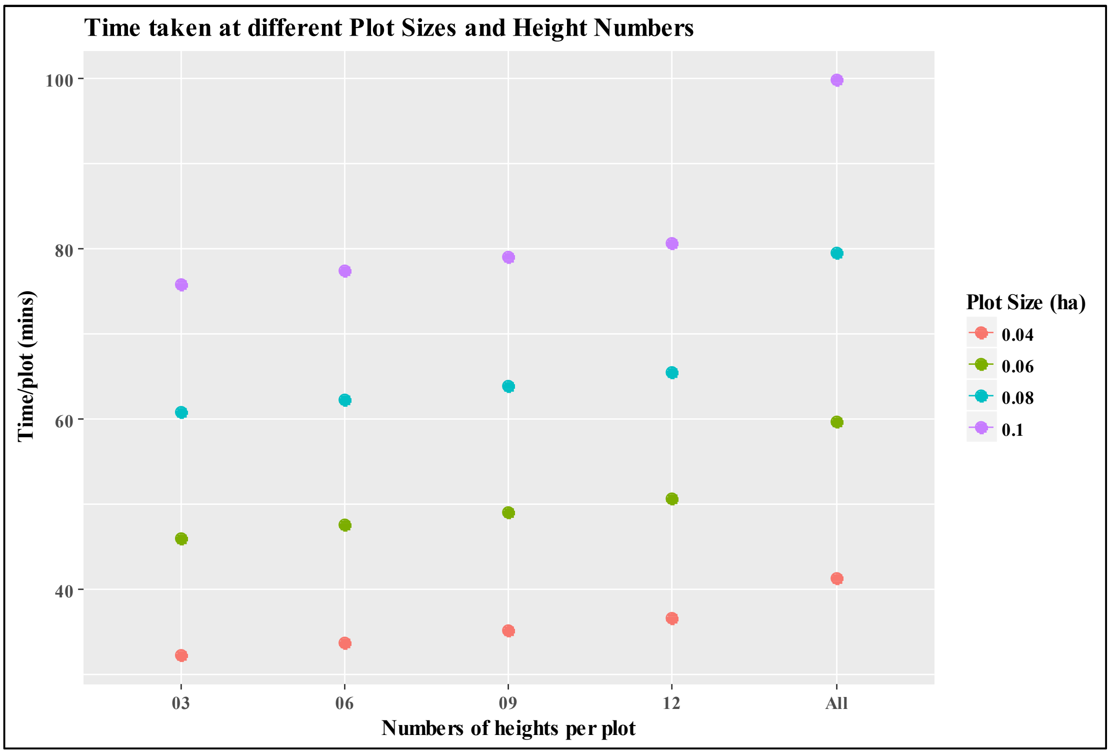

Figure 3: Times for measuring a range of plot sizes and numbers of height trees measured to fit H-D relationship per plot.

Table 10: Average times per plot generated from time study conducted for all 20 variations of plot size and height numbers measured per plot.

Plot Size (ha)	Number of heights measured per plot	Time (minutes)
0.04	3	32.2
0.04	6	33.7
0.04	9	35.2
0.04	12	36.6
0.04	All	41.2
0.06	3	45.9
0.06	6	47.5
0.06	9	49.0
0.06	12	50.1
0.06	All	59.7
0.08	3	60.7
0.08	6	62.2
0.08	9	63.9
0.08	12	65.4
0.08	All	79.6
0.10	3	75.8
0.10	6	77.4
0.10	9	79.0
0.10	12	80.6
0.10	All	99.9

A linear mixed effects model for time taken per plot was analysed with plot size and number of heights measured per plot as factors and with plot id as a random variable. The results of the analysis of variance are displayed below in *Table 11*. It is evident that both number of heights measured per plot and plot size were statistically significant variables with P values much less than 0.05, being both $2.2e^{-16}$.

Table 11: Analysis of variance for linear mixed effects model for time taken per plot with plot size and number of heights measured per plot as factors, and plot id as a random effect.

	Chi Square	Degrees of Freedom	P Value
Plot size	5213	3	< 2.2e-16
Number of heights measured	583	4	< 2.2e-16

Furthermore, pairwise comparison tests were conducted to test where the significant difference occurred in the time to measure a plot for each of the factors. The following outputs *Table 12* and *13*, below, show the groupings for the different numbers of heights measured per plot and plot sizes, respectively. It can be seen that for each of the factors, all observations are significantly different from one another. It can therefore be said that increasing the numbers of heights measured per plot in increments of three trees has a statistically significant effect on the time taken per plot, as does increasing the plot size. However, the previous graph, *Figure 3*, above, showed that there were smaller increases in the time taken as the number of height trees measured per plot increased in increments of three than there were for increases in plot size in increments of 0.02 ha.

Table 12: Pairwise comparison test for time taken to measure a plot with numbers of heights measured per plot as the factor.

Number of heights measured	Emmean	Std. Error	Degrees of Freedom	Lower Confidence Limit	Upper Confidence Limit	Group
3	53.7	2.42	24	48.7	58.7	A
6	55.2	2.42	24	50.2	60.2	AB
9	56.8	2.42	24	51.8	61.8	BC
12	58.3	2.42	24	53.3	63.3	C
All	70.1	2.42	24	65.1	75.1	D

Table 13: Pairwise comparison test for time taken to measure a plot with plot size as the factor.

Plot Size (ha)	Emmean	Std. Error	Degrees of Freedom	Lower Confidence Limit	Upper Confidence Limit	Group
0.04	35.8	2.41	24	30.8	40.7	A
0.06	50.5	2.41	24	45.6	55.5	B
0.08	66.4	2.41	24	61.4	71.3	C
0.10	82.5	2.41	24	77.6	87.5	D

Discussion

Plot Size

There was no reduction in standard deviation for stocking, basal area, volume and mean top height as plot size increased from the current standard size of 0.04 ha to the largest plot extent measured of 0.10 ha. This indicates that there was very little change in the forest structure at a micro level, and the within forest variation occurred at larger scales. Increasing the plot size was hypothesised to have allowed more site variation to be accounted for, thus providing more accurate estimates of each parameter as the plot size measured increased, but this hypothesis was false.

However, while there were no statistically significant increases in standard deviation, there were significant differences due to both plot size and numbers of heights measured/plot when accuracy was considered. This accuracy by means of the absolute value of error in MTH estimation indicated that there was practical potential in the measurements of larger plot sizes for precision forestry in the stand studied, however, it is probable that it would be more effective in the case of Omihi Forest to measure more plots per stand than to measure larger plots per stand.

Stand Level vs Plot Level

The previous study by Mason (2018) indicated that fitting the H-D relationship at a stand-level artificially reduced the error of estimates of MTH and this is supported by the findings of this study. The results highlight that the trends of standard deviation of MTH being lower for fittings at stand-level was misleading and simply a function of the stand-level method of estimating heights, whereas fitting the H-D relationship fitting at a plot-level allowed for more realistic variability estimates. For studies of site variation H-D relationships should be fitted at a plot level. A number of factors influence the productivity of a site such as elevation, slope, soil and aspect, and fitting H-D relationships at a plot-level allows for different H-D relationship patterns between plots.

Number of height trees measured

A key finding throughout this study was that there is potential to reduce the absolute value of error for estimations of MTH by increasing the number of height trees measured. In addition, the absolute value of error of MTH estimations could also be decreased by measuring larger plots. These results apply only to the study location and it should not be assumed that all stands even within Omihi forest will produce similar, or the same results. However, as site index is often used to characterise variation in site productivity, gaining accuracy is important, and should be considered by managers designing inventories.

The linear mixed effects model for MTH estimations with numbers of heights measured per plot and plot size as factors with plot id as a random variable showed that number of heights measured per plot had a statistically significant effect on the value of the MTH estimation. Pairwise comparison tests that this statistical difference occurred between three heights measured, and the other numbers of heights measured per plot. Since the MTH estimation with all trees measured should be representative of the true plot MTH, it can be said that increasing the number of heights measured per plot to six or more creates a more realistic MTH estimation than measuring three heights per plot. The implications of this result extend into the reaches of precision forestry, which requires a more intensive inventory than current PHI practices are standardised as.

Moreover, the result suggests that MTH estimation at a plot level with very few heights may have produced biased estimates. Reasons for this bias are unclear.

Cost

The time taken for each inventory method was found to be more influenced by plot size than by the number of height trees measured to fit the H-D relationship. This extra time arose from the extra number of trees being measured as well as the extra distance required for the crew to walk in order to both set up the plot and to navigate around to measure each tree. There was a much smaller increment in time for measuring more heights. As time/plot is not greatly affected by the number of heights measured between three and 12 per plot, and that more height measurements confer statistical advantages, managers should consider measuring more heights per plot during inventories. However, there are diminishing returns to extra height measurement as measuring all trees in any given plot size had a large effect on the time of measurement with little change in the estimation of the MTH.

LiDAR

While Rayonier Ltd. gather LiDAR data for many of their forests, the most recent remotely sensed data available for Omihi Forest were collected in 2016. Morgenroth (personal communication, 2018) suggested that any LiDAR data more than two years older than the stand ground measurements should not be assumed to be the same resource because that two years of growth is enough time to add a significant amount of error to the LiDAR metrics when fitting a regression. Essentially, trees can die and unpredictable growth can occur within this timeframe, reducing the utility of LiDAR data. For the immediate future, it is likely that forestry companies will continue to rely on ground-based inventory because LiDAR can be expensive to deploy. However, given that LiDAR requires a full height capture in order to regress the point cloud metrics, and in accordance with precision forestry, there may be real benefits of increasing the number of heights measured per plot that extend beyond the limitations of inventory efficiency.

Limitations

This study had a number of limitations. A key limitation was the amount of time required in order to intensively measure the full extent of all plots. Given that a PHI was conducted earlier in the year, there was a systematic plot layout already established for a 0.04 ha plots. In order to save a large amount of time, and therefore cost, the data from the PHI were utilised as they were not deemed too far out of date. By using this pre-laid plot system, the study was limited to a low number of sampling units of 25. However, if more plots had been studied there would have been a substantially increased cost of inventory and also time taken. While it is expected that 25 plots should provide a fairly good idea of the spatial distribution of tree growth and form variables for the stand, the study could have been improved by measuring a much greater number of plots, and so it should be regarded as a pilot study.

The sampling method using plot sizes of 0.1 ha meant that for some full-sweep plots at a size of 0.04, mirage was required for 0.1 ha as they overlapped the boundary at the larger plot size. This meant that mirage was conducted for a small handful of plots, where the plot centre may have fallen on a row of trees, meaning some plots had a double count for two or three trees which should not have been counted. This very likely influenced estimates of variability between plots. Another limitation surrounding the plot measurement is that generally not all trees are in fact measured for distance; the number measured will vary by plot. While this adds a limitation the time study, it makes the times per plot more conservative. Moreover, as mirage plots involve re-using measurements within a plot, the impacts of mirage methods on variability should be studied.

The study was limited to Omihi Forest. Due to the rather specific environment that is found in this forest, with low competition, tougher growth conditions which arise from saline wind off the coast, and the rolling terrain, the results from this study should be considered specific to Omihi Forest. However, the trends and some assumptions made can be investigated for other forests as this study acts as a pilot study.

The time study conducted on the crew was performed for 12 of the 25 plots recorded, therefore, while there was a large sample of trees involved in the time study, not all independent sampling units were represented when fitting the expected times taken per plot with and without height measurements. Further to the number of observations measured in the time study, only a portion of the trees within those plots of which the time study was conducted upon were represented. This arose due to the initial PHI which was conducted earlier in the year. Because the key variables were already measured, it was sensible to utilise this data, and so, there were no times to record for any tree within the 0.04 ha boundary for any of the timed plots.

Conclusion

The first key question that was addressed in this study was "*what is the relationship between plot size and standard deviations of basal area/ha (G), stems/ha, mean top height (MTH) and stem volume within an inventory?*" It was found that while the lowest overall standard deviation occurred at the largest plot size, there were no statistically significant differences between the standard deviations for each plot size for each of the four key variables.

The next key research question that was posed for this study was "*what is the relationship between plot size and numbers of heights measured/plot and cost of measurement/plot?*" While there was no direct application for cost of the inventory given that the rate was unknown, the cost for inventory was defined as the time taken. Increasing plot size had a large effect on the time taken to measure a plot, indicating that increasing plot size did not decrease the standard deviations of the key variables between plots enough to justify the significant increase in cost of inventory. With the number of heights measured per plot, it was found that increasing this had an effect on the time taken, albeit, the effect was of a much less extent than for plot size.

The final key research question was "*are there statistical, financial and/or practical benefits in measuring more heights per plot for inventory of a stand?*" The main variable that is affected by the changing number of measured heights per plot is MTH. Increasing the number of heights measured per plot did not provide significantly lower standard deviations in the estimation of MTH. However, it was found that there was a statistically significant decline in the absolute value error of MTH estimations as number of height measurements increased. Increasing the number of heights led to more realistic estimations of MTH through a lower mean absolute value of error. While this trend was only prevalent for one specific plot size, 0.08 ha, if we increased the number of plots measured in the study from the current number of 25, we would expect that the trends expressed in the 0.08 ha plots might become more significant for the other plot sizes too (i.e.: a type II error may have occurred). There was strong evidence that measuring more than 3 height trees per plot provided a significantly lower absolute value of error of MTH estimation than measuring only 3. This trend was also replicated for the estimates of MTH, where measuring 3 heights per plot provided significantly different estimates of MTH compared to measuring 6 or more. Given all heights measured should represent the true MTH, having 6 heights measured per plot be not statistically different indicates that there is merit to measuring up to 6 heights per plot.

Increasing the number of trees measured to fit H-D relationships did not have a large effect on the time taken to conduct the inventory. This provides some incentive to increase the number of heights measured given the significant decrease in absolute value of error of MTH estimation when measuring more than 3 height trees, particularly if companies are interested in defining local changes in site quality through implementation of precision forestry principles.

Increasing the number of heights measured provides the added benefit of being able to formulate better LiDAR canopy metrics through regression with the ground measured variables. In order to fit effective LiDAR canopy metrics, a full height capture is generally required, or at least a more intensive height capture in order to derive a sturdy H-D relationship that explains as much variation as possible. It is also noted that fitting an H-D relationship at plot-level, as is done for Permanent Sample Plots (PSPs), requires more measured heights. The reason why stand-level fittings are done is because three trees per plot is not considered enough to fit a robust H-D relationship that accounts for the large amount of variability in height for larger diameter trees, showing an asymptotic trend. Another practical benefit of this more realistic estimation of MTH is for site-specific productivity measurements such as site index, which is built from the MTH. Having more realistic MTH estimations provides the forest manager with a greater understanding of their forest and allows them the flexibility to make more optimal management decisions.

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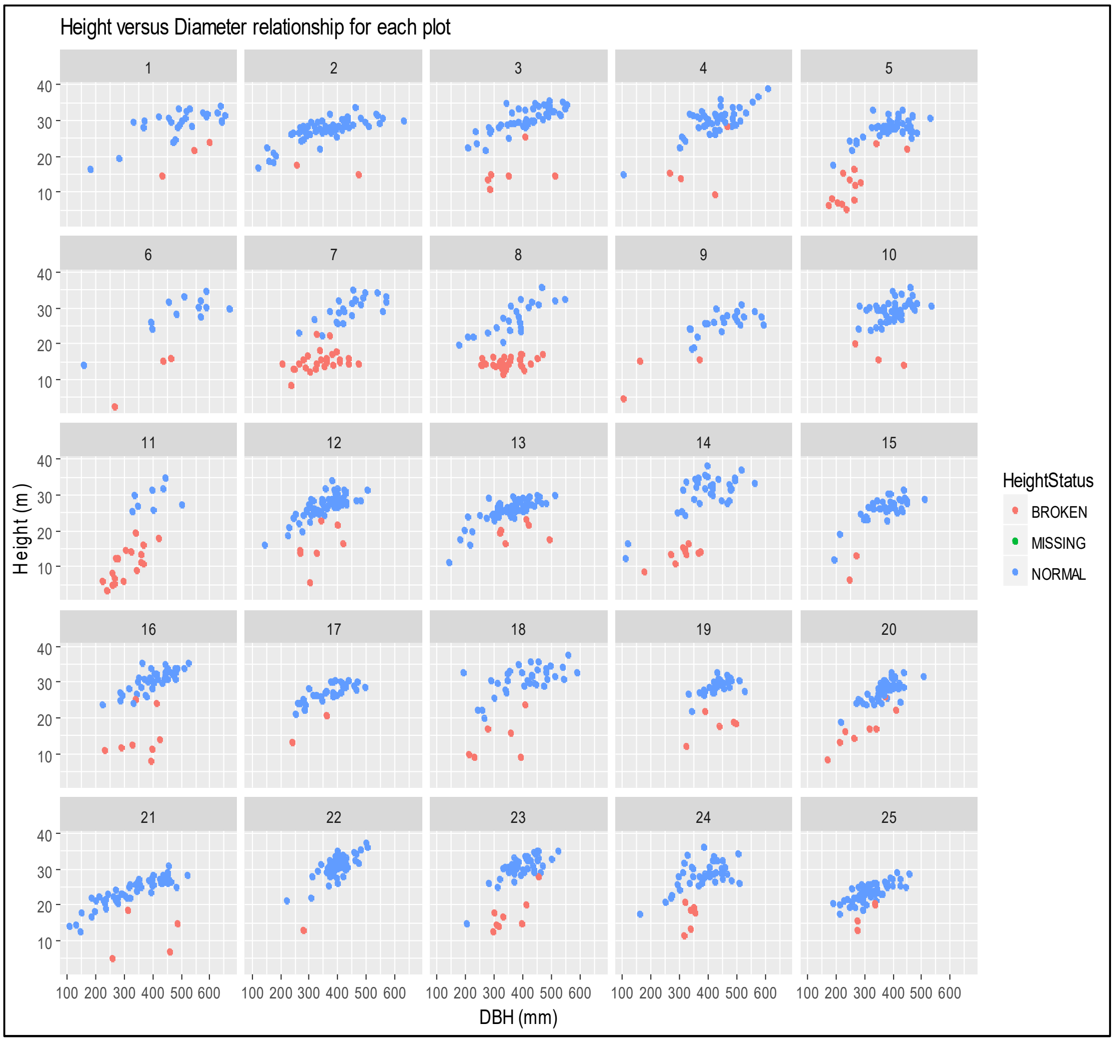
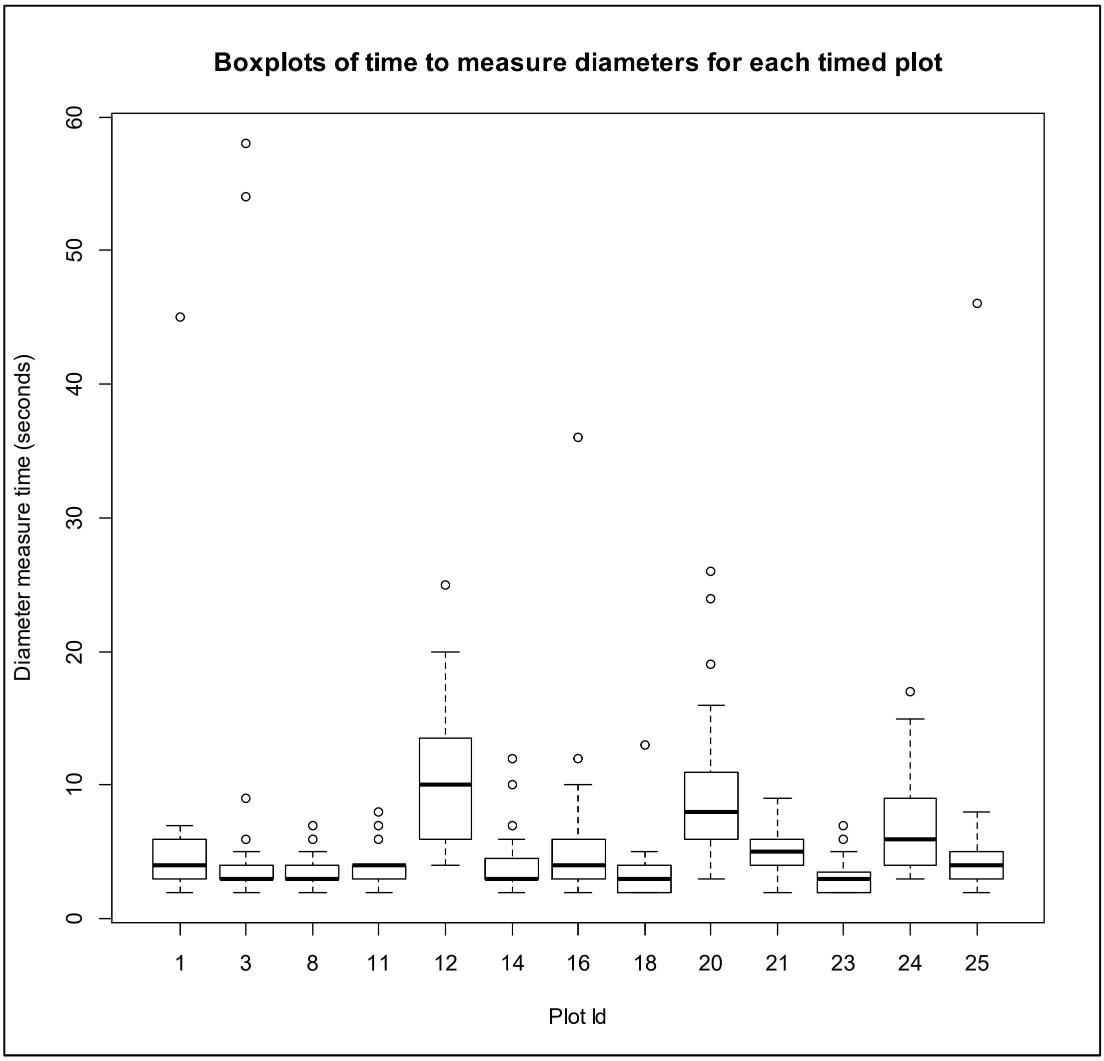
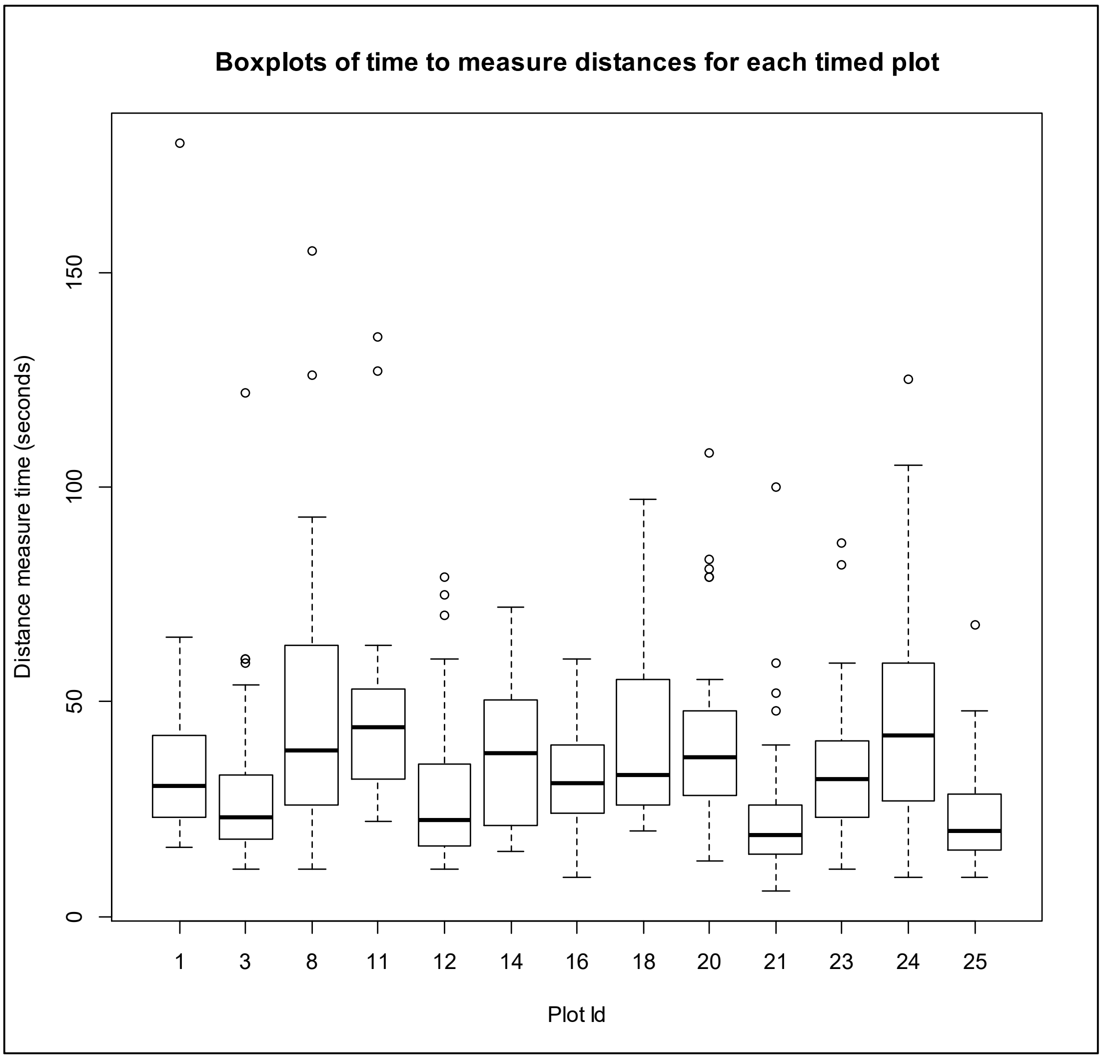
Appendices



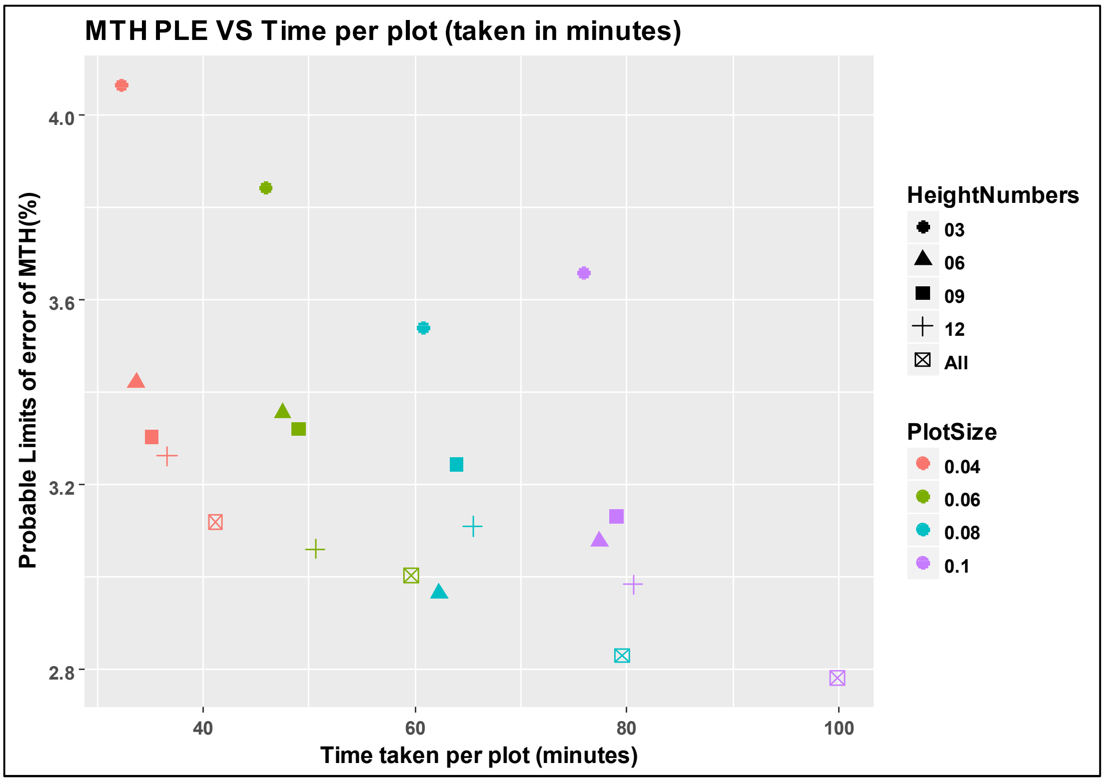
Appendix 1: Height versus diameter relationship for each plot where the status of the height is factored.



Appendix 2: Boxplots of distributions of time taken to measure the diameters for each of the 12 timed plots.



Appendix 3: Boxplots of distributions of time taken to measure the distances for each of the 12 timed plots.



Appendix 4: PLE vs time per plot in minutes for each number of heights measured and plot size. Note: PLE is statistically not significant, however, interesting trends are observed.